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ESTIMATING SOLAR RADIATION FOR PLANT SIMULATION MODELS

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16. Abstract <p>There is considerable interest in using plant growth simulation models for large area yield forecasting in the United States and foreign areas. These models generally require daily input values of solar radiation, temperature, and rainfall. For calibration and evaluation of these models, historical data are needed. However, historical solar data are rarely available because solar radiation has been measured at only a few locations, frequently for only limited time periods. It would be necessary to develop surrogates for the historical data values.</p> <p>Five algorithms producing daily solar radiation surrogates using daily temperatures and rainfall were evaluated using measured solar radiation data for seven U.S. locations. The algorithms were compared both in terms of accuracy of daily solar radiation estimates and in terms of response when used in a plant growth simulation model (CERES-wheat). Requirements for accuracy of solar radiation for plant growth simulation models were discussed. One algorithm was recommended as being best suited for use in these models when neither measured nor satellite estimated solar radiation values were available.</p>					
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INTRODUCTION

Large area yield forecasting for the United States and foreign areas is an application of plant growth simulation models with great potential. Forecasts from these models could be a powerful tool for agricultural and economic policy makers in both government and industry.

Daily solar radiation data are required in most models. Until recently, solar radiation had been measured at only a few locations around the world. Because of the lack of available data, various surrogates for measured solar radiation are being developed and tested for use in the models. Recently, satellite estimated solar radiation became available for most of the Western Hemisphere on a "real-time" basis. If satellite data can be used to produce accurate solar radiation estimates, one obstacle to using simulation models for large areas or many locations would be removed.

Calibration of a particular crop growth simulation model would be needed for area-specific factors: soil fertility, water holding capacity, varietal characteristics, fertilizer and pesticide applications, planting practices, and other management practices. This calibration also requires historical yield and meteorological data including solar radiation data for that area. Because historical solar radiation data are not generally available, a surrogate must be used. In this paper five algorithms are compared for producing solar radiation surrogates from commonly measured daily meteorological variables.

As used in this paper, a solar radiation "surrogate" will produce solar radiation data which is similar to observed data in terms of various statistical measures: similar daily mean, similar variability, etc. These surrogates are not intended to accurately predict observed

1 data on any given day. The term "estimate" is reserved for accurate
2 daily predictions, and estimates of yearly yield.

3 SOLAR RADIATION ALGORITHMS

4 Five algorithms producing surrogate measures of solar radiation
5 are compared in this study. They are referred to as CE, SR, R0, R1, and
6 R2. The CE algorithm (Cengiz et al, 1981) was developed using data from
7 Columbia, Missouri. It is composed of two types of functions. Location
8 specific functions require information on latitude. Daily functions
9 require the day of the year and daily maximum and minimum temperature
10 (Table 1a).

11 The SR, R0, R1, and R2 algorithms are based on the Richardson
12 (1981) weather simulation model (Table 1b, c, d, e). The Richardson
13 model uses a set of location specific constants to estimate daily rain-
14 fall, solar radiation, and maximum and minimum temperature. These
15 constants would be available only for locations in the continental
16 United States. The solar radiation and temperature values are estimated
17 as daily deviations from annual curves. The annual curves consist of
18 long term average daily values. Separate curves are used for dry days
19 and for rainy days. Rainy days are defined as those days for which
20 rainfall has been estimated as being greater than zero. The algorithms
21 used in this study modified Richardson's model so that observed tempera-
22 tures and rainfall were used to estimate solar radiation.

23 The SR algorithm (Table 1b) was based only on Richardson's annual
24 curves for normal radiation. Separate curves were used for dry days and
25 for rainy days. There were no daily deviations from the annual curves.

26 To estimate daily deviations from the annual curve values for solar
27 radiation, temperature, and precipitation, the Richardson model uses

1 correlations, one day lag correlations and a random component. The
2 correlations and one day lag correlations were reported to be approxi-
3 mately uniform for the continental U.S. (Richardson, 1981). It may be
4 acceptable to extend these correlations to other regions. In the R0
5 algorithm, the actual deviations of maximum and minimum temperatures and
6 the correlations were used to estimate the daily deviation of solar
7 radiation (Table 1c).

8 The R1 and R2 algorithms also use Richardson's correlations among
9 daily deviations of temperature and solar radiation. These correlations
10 and the actual daily deviations of maximum and minimum temperatures are
11 used to produce daily deviations of solar radiation in the R1 algorithms
12 (Table 1d).

13 Because the daily variability of solar radiation estimated by R1
14 was too small, the daily deviations of SR were amplified for the R2
15 algorithm (Table 1e). The amplification was moderate for deviations
16 above the annual curves but greater for deviations below the annual
17 curves. Measured data (DOE, 1979) from St. Cloud, MN; Rapid City, SD;
18 and Glasgow, MT were used to determine the degree of this amplification.
19 Richardson's annual mean values of solar radiation were changed by the
20 amplification. The new "annual mean values" were approximately 5%
21 greater than the actual values for dry days and 15% greater for rainy
22 days.

23 DATA

24 The SOLDAY (DOE, 1979) data set encompasses the period 1952-1974.
25 It consists of measured and rehabilitated (adjusted for known procedural
26 and instrumental errors) daily solar radiation values and associated
27 maximum and minimum daily temperatures and rainfall for 27 U.S.

1 stations. The rehabilitated solar radiation data were viewed as
2 "ground truth" for the purposes of this study. Seven stations (Table 2)
3 were selected to compare the five algorithms producing solar radiation
4 surrogates for the rehabilitated solar radiation values. Three of the
5 seven stations (St. Cloud, Rapid City, and Glasgow) had been used in the
6 development of the R2 algorithm. Seven surrogate data sets, one for
7 each station, were developed for comparison with ground truth (Table 2).

8 When the rehabilitated and simulated solar radiation values were
9 compared over the seven stations, several things became apparent. Some
10 of the rehabilitated solar radiation values were obviously too large
11 (greater than 85% of solar radiation at the top of the atmosphere). The
12 R2 and the CE algorithms also occasionally estimated excessively high
13 values, the CE algorithm more so than R2.

14 The SOLDAY (DOE, 1979) data also included daily values of solar
15 radiation at the top of the atmosphere and the percent possible
16 transmissivity of the atmosphere for each location.

17 For use with the yield model, the rehabilitated solar radiation
18 values, the R2 algorithm values, and the CE algorithm values were
19 screened for values greater than maximum potential. This maximum was
20 defined to be the product of percent possible atmospheric transmissivity
21 (%T) and solar radiation at the top of the atmosphere (ETSR). Values
22 higher than this maximum were reduced to the maximum. This screening
23 algorithm reduced the observed solar radiation values by an average of
24 0.7%, the R2 algorithm values by an average of 0.5%, and the CE algorithm
25 values by an average of 1.0%. Values from the R0, R1, and SR algorithms
26 were not affected by the screening.

27

COMPARISON METHODOLOGY

The surrogates of solar radiation could themselves be compared to the rehabilitated ground truth data to determine which was the best estimate. These surrogates were developed solely for use in simulation models, however. Because of this, it was felt that their impact on yield prediction in the models would be the important criterion. The best algorithm would not necessarily be the one which produces the best estimates of ground truth but rather would be the one which produces similar yield predictions when used in a simulation model.

The Ceres-wheat model (Ritchie and Godwin, 1983; Otter, Ritchie and Godwin, 1983) was the model selected for comparison of the five solar surrogates. This program requires initial parameter values for initial soil water content, soil water retention characteristics, variety of wheat (Triticum aestivum L.) planting density and depth, planting date, and latitude.

Model estimates were derived using data from three of the SOLDAY stations: St. Cloud, Minnesota; Rapid City, South Dakota; and Glasgow, Montana. Both continuous cropping and summer fallowing practices were used. Median planting dates for each year at each station were estimated using a spring small grains planting date model (Hodges and Artley, 1981). Daily values of rainfall and maximum and minimum temperature were required for each station.

The solar radiation input was first supplied by the rehabilitated ground truth data. Five additional model estimates were generated with identical inputs for all variables except solar radiation. For each of these, data estimated using one of the solar radiation algorithms were used. The model was also run using unscreened values from the

1 ground truth solar radiation and from the R2 and CE algorithms. On the
2 average, yields were reduced by less than 1% compared to model estimates
3 using screened data.

4 The resulting predicted yields using each of the solar surrogates
5 could then be compared to yields predicted using the ground truth data.
6 The algorithm which led to results most similar to that using ground
7 truth data could then be determined. The sensitivity of the model to
8 variations between the algorithms could also be studied.

9 For the algorithm comparison, the yearly difference (D) between
10 ground truth yield predictions (GTY) and predictions using each surro-
11 gate (EST) would be calculated:

$$12 \quad D = GTY - EST.$$

13 The arithmetic mean of D would indicate the bias of the yield
14 estimates. Smaller bias measures would imply better surrogates. Bias
15 values would be calculated for each algorithm for each station for
16 continuous cropping and for summer fallow, a total of thirty values.

17 It would also be important for the root mean square error, RMSE, to
18 be small to indicate that more estimates have a small D value than a
19 large one. This statistic is calculated by:

$$20 \quad RMSE = \sqrt{D^2/n}.$$

21 The standard deviation of the D values (SD) is also calculated.
22 This indicates what the RMSE would be if the bias were removed.

23 Maximum values of D (MAX D) and minimum values of D (MIN D) would
24 also be compared. As a final measure of the similarity between GTY and
25 EST, the Pearson correlation coefficient, CORR, would be determined.

26 COMPARISON RESULTS

27 Statistics used for comparison of yield predictions using each of

1 the five solar radiation surrogates are shown in Table 3. Mean and
2 standard deviations of yield predictions using the rehabilitated solar
3 radiation data (GT) were compared to predictions using each solar
4 surrogate.

5 In half of the cases, R2 produced yield estimates most similar to
6 those using ground truth data. SR was nearest in one third of the cases.
7 The CE algorithm had the highest bias generally. The SR algorithm had
8 a standard deviation of the estimates nearest to ground truth. R0 was
9 the poorest in terms of similar variation.

10 The RMSE values indicate that the R2 algorithm produced yield
11 estimates which had less variation around ground truth, followed by CE.
12 R0 again was the poorest. If the bias were removed, the SD values show
13 that the CE algorithm would have been least variable. R0 was, again,
14 the poorest. The bias, being a function of the model's sensitivity to
15 solar radiation, would be difficult to remove.

16 The range of the data, shown by MAX D and MIN D, indicates that for
17 St. Cloud, MN summer fallow, all of the algorithms except R2 produced
18 estimates which were too low in all of the years. For other areas, the
19 ranges are comparable.

20 The correlation values indicate the closest correspondence between
21 CE yield estimates and ground truth. R0 and R2 did poorest using this
22 criterion.

23 Although "best" and "worst" surrogates could be detected, all were
24 very close. Each would be acceptable in terms of the correlation of
25 their predicted yields with those yields predicted using the
26 rehabilitated solar radiation data. Differences between indicators for
27 summer fallowed and continuous cropped were generally negligible.

DISCUSSION

The magnitude of day to day variability of solar radiation would be more critical than day to day accuracy. This is due to the strong effect of solar radiation on the modeled soil water balance. When ample soil moisture is available, evaporation occurs at an "energy-limited" rate proportional to the energy available from solar radiation. When the modeled water content of the soil surface is depleted more than a certain amount (U), direct evaporation of water from the profile (excluding transpiration) occurs at a rate roughly proportional to the square root of the number of days on which drying has occurred. This "time-limited" evaporation rate is generally much lower than the energy-limited evaporation rate. On rainy days, $4/5$ of the rainfall is available for evaporation at the "energy-limited" rate even if the surface water depletion is greater than U . On the next dry day, moisture that has entered the profile is evaporated at the "time-limited" rate if the surface water depletion is greater than U . Consider that in a dry situation when a small amount of rainfall occurs, moderate or high solar radiation will cause near total evaporation. However, low solar radiation will allow most of the rain to enter the soil profile and be subject to "time-limited" evaporation. Thus, on two days with small amounts of rainfall, daily solar radiations of 700 and 100 langleyes respectively would allow considerably more water to enter the profile than would two days of 400 langleyes each.

In the Ceres-wheat model, carbon fixation is affected by solar radiation in a nonlinear fashion. For radiation amounts to 467 langleyes/day of intercepted light, carbon fixation is proportional to light. At higher light intensities, no additional carbon is fixed.

1 Uniformly moderate solar radiation (as opposed to highly variable solar
2 radiation) will result in more biomass accumulation, more leaf growth,
3 more water use, and under moist conditions, higher yield. However, with
4 dry conditions, more water stress and lower yield will result.

5 CONCLUSIONS

6 Although the differences between algorithms were small, the bias
7 and root mean square error indicated that the R2 algorithm would be
8 recommended as a solar radiation surrogate for use in simulation models.
9 When used in the Ceres-wheat yield model, the R2 solar radiation surro-
10 gate produced yield predictions closest to those using ground truth
11 solar radiation data. The CE algorithm also produced close estimates,
12 but had a larger bias which would be difficult to remove as it is a
13 function of the model's sensitivity to solar radiation.

14 The R2 algorithm would also be recommended for use in foreign areas.
15 The location specific coefficients for the R2 algorithm can be derived
16 from long term average monthly solar radiation values; these would be
17 available world-wide (de Jong, 1973). Only an assumption about the
18 average difference between solar radiation on rainy days and on dry days
19 for a location would be needed for use of this surrogate. Because of
20 this, the R2 algorithm would be recommended for use in areas for which
21 neither measured nor satellite estimated solar radiation values are
22 available.

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1 Table 1. Equations for Solar Radiation Simulation Algorithms

2 a. CE Algorithm (Cengiz et al, 1981)

3 Solar Radiation = $49.03 + .1 * FIS - 7.26 * DBR$
 4 $+ .06 * FIS * DBR$

5 Location specific functions:

6 $S = \sin (\text{Latitude} * \pi / 180.)$

7 $T = \tan (\text{Latitude} * \pi / 180.)$

8 $C = \cos (\text{Latitude} * \pi / 180.)$

9 $SLD = \arcsin ((.5 + .007895/C + .2168875 * T)^{1/2}) * 180./ \pi$

10 $SN = \sin (\pi * SLD / 24.)$

11 $A = (S * (46.355 * SLD - 574.3885) + 816.41 * C * SN)$
 12 $* (.29 * C + .52)$

13 $B = (S * (574.3885 - 1.509 * SLD) - 26.59 * (C * SN) * (.29 * C + .52))$

14 Daily Functions:

15 $SI = \sin (2 \pi / 365. * (\text{JULIAN DATE} + 10.5) - 1.5708)$

16 $FIS = A + B * SI$

17 $DBR = (TX - TN) * 5/9$

18 b. SR Algorithm (Richardson, 1981)

19 Solar Radiation = $RM(I) + AR * \cos (.0712 * (\text{Julian Date} - 172))$

20 RM (1) = Annual mean solar radiation for dry days

21 RM (2) = Annual mean solar radiation for rainy days

22 AR = Amplitude of annual solar radiation curve

23 For dry days, I = 1; for rainy days, I = 2

24

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Table 1 (continued)

c. RO Algorithm (largely based on Richardson, 1981)

$$\text{Solar Radiation} = \text{SRL} * \text{SRSD} + \text{SRBAR}$$

If Solar Radiation < 0.0 then Solar Radiation = 0.0

If Solar Radiation > 770. then Solar Radiation = 770.

Location specific constants:

TXM (1) and TXM (2) = mean annual maximum daily temperatures for dry days (1) and wet days (2).

ATX = Amplitude of annual curves (dry day and wet day) daily maximum temperature

CVTX = coefficient of variation of daily deviations of maximum temperature from annual curves

ACVTX = coefficients of variation of ATX

TNM = mean annual daily minimum temperature

ATN = Amplitude of annual curve of daily minimum temperature

CVTN = coefficient of variation of daily deviations of minimum temperature from annual curve

ACVTN = coefficient of variation of ATN

RM (1) and (2) = mean annual daily solar radiation for dry days (1) and rainy days (2)

AR = amplitude of annual curves of daily solar radiation

CVR (1) and (2) = coefficients of variation of daily deviations of solar radiation from annual curves for dry days (1) and for rainy days ACVR (1) and (2) = coefficients of variation of AR for dry days (1) and for wet days (2)

Table 1 (continued)

Daily functions:

$$SRSD = ABS (SRBAR * (CVR (I) + ACVR (I) * DR))$$

$$SRBAR = RM (I) + AR * DR$$

A and B are matrices (3 x 3) derived by Richardson to describe the intercorrelations between daily maximum and minimum temperatures and solar radiation in the continental United States.

I = 1 for dry days or I = 2 for rainy days

$$ASRL = A (3,1) * PTXL + A (3,2) * PTNL + A (3,3) * PSRL$$

where PTXL, PTNL, and PSRL are TXL, TNL, and SRL values from the previous day

$$DT = Cos (.0172 * (Julian date - 200))$$

$$DR = Cos (.0172 * (Julian date - 172))$$

$$TXBAR = TXM (I) + ATX * DT$$

$$TXSD = ABS (TSBAR * (CVTX + ACVTX * DT))$$

The above equations are from the Richardson (1981) weather simulation.

The following five equations were developed to adapt the weather simulator to estimate only solar radiation:

$$SRL = ASRL + B (3,1) * TXL + B (3,2) * TNL$$

$$TXL = (TX - TXBAR)/TXSD$$

If TXL > 1.5 or TXL < -1.5 then TXL = 0.0

$$TNL = (TN - TNBAR)/TNSD$$

If TNL > 1.5 or TNL < -1.5 then TNL = 0.0

d. R1 Algorithm

Same as R0 algorithm except:

$$SRSD = .25 * SRBAR$$

$$TXSD = 9.$$

$$TNSD = 9.$$

Table 1 (continued)

R2 Algorithm

Same as R0 algorithm except:

$$\text{Solar Radiation} = \text{Noise} * \text{SRL} * \text{SRSD} + \text{SRBAR}$$

$$\text{SRSD} = .1 * \text{SRBAR}$$

$$\text{TXSD} = 14.$$

$$\text{TNSD} = 14.$$

where Noise = 4.4 for $\text{SRL} > 0.0$ on dry days

= 11.44 for $\text{SRL} \geq 0.0$ on rainy days

= 13.2 for $\text{SRL} < 0.0$ on dry days

= 34.32 for $\text{SRL} \leq 0.0$ on rainy days

If Solar Radiation > 770.1 y/day then Solar Radiation = 770.

RM (1) and RM (2) should be approximately 5% and 15% greater than the actual annual mean daily solar radiation for dry days and rainy days respectively.

Table 2. Statistics for comparison of solar radiation estimates to ground measured solar radiation (GT)

[illegible]

Table 3. Statistical Comparison of Yield Estimates
from the CERES-Wheat Model Using the
"Ground Truth" Data (GT) and Estimates
Using Each of the Algorithms for Solar
Radiation Surrogates in the Model

St. Cloud, MN

n = 20

		MEAN	BIAS	STD	RMSE	SD	MAX D	MIN D	CORR
7	Summer Fallow								
8	GT	3193	--	601	--	--	--	--	1.000
9	R0	3574	-381	625	445	237	-5	-1051	.926
10	R1	3591	-398	630	461	238	-40	-1084	.926
11	R2	3078	115	672	263	242	690	-250	.934
12	CE	3607	-253	629	288	142	-15	-615	.919
13	SR	3446	-414	587	480	248	-45	-1121	.972
14	Continuous Crop								
15	GT	3150	--	633	--	--	--	--	1.000
16	R0	3508	-358	704	439	262	157	-1031	.929
17	R1	3530	-379	708	455	258	138	-1065	.932
18	R2	3060	90	669	277	268	690	-372	.917
19	CE	3356	-206	665	293	214	358	-596	.947
20	SR	3532	-382	722	474	288	229	-1098	.918

Table 3 (continued)